

# Music Genre Classification



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# Motivation + Problem Description

- Spotify have listed over 50 million songs and over 40 thousand new songs are added every day
- Increasing interests towards Music Information Retrieval (MIR)
- Lots of work done in Music Genre Classification



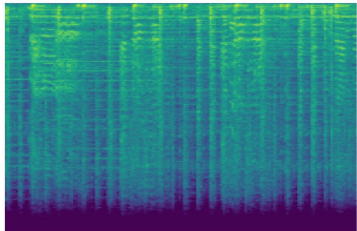
## Genre Classification:

- Use extracted features from audio to accurately classify the genre

Table 1: Results on GTZAN

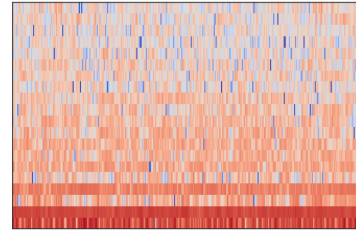
Model	Feature	Accuracy
MusicRecNet + SVM [1]	Melspectrogram	97.6%
Broadcast NN [2]	Melspectrogram	93.9%
CNN + 1-layer RNN [8]	STFT	90.2%
CNN + 2-layer RNN [8]	STFT	88.8%
CNN [8]	STFT	88.0%
2-layer BRNN [4]	STFT	76.2%

# Representations of Music



(a) STFT

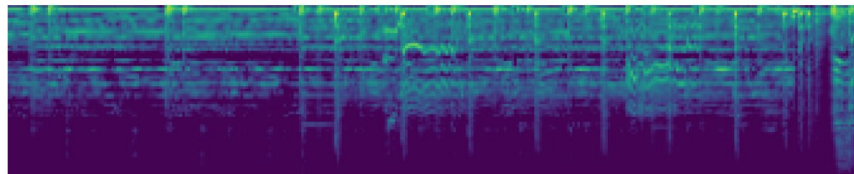
- Short-time Fourier Transform
- Sinusoidal frequency and phase content of local sections of a signal as it changes over time
- Process: Divide longer time segment into shorter equal segments and compute the Fourier transform separately on each segment. This shows the Fourier spectrum on each segment and then together plotted as a function of time



(b) MFCC

- Mel-frequency cepstral coefficients
- MFCCs are coefficients that make up a Mel-frequency cepstrum (MFC)
- Derived from a type of cepstral representation of audio
- Approximates the human auditory system response more closely than others and allows for a better representation of sound.

# Representations of Music cont.



(c) Melspectrogram

- Essentially a spectrogram (frequency vs time) in mel scale
- Mel scale is a logarithmic transformation of a signal's frequency
- Mel scale basically mimics our own perception of sound

# Data

## GTZAN [7]

- 10 genres; 100 songs of 30 seconds length for each; Total: 1000
- Blues, Classical, Country, Disco, Hiphop, Jazz, Metal, Pop, Reggae, Rock

## Extended Ballroom [3]

- 13 genres (4 removed for < 70 samples); 250 - 530 songs for each; Total: 3,992
- Chacha, Jive, Quickstep, Rumba, Samba, Tango, Viennese waltz, Waltz, Foxtrot

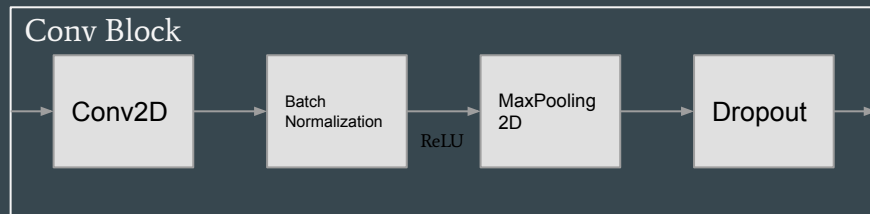
5, 8, 10 segments

6 sec, 3.75 sec, 3 sec

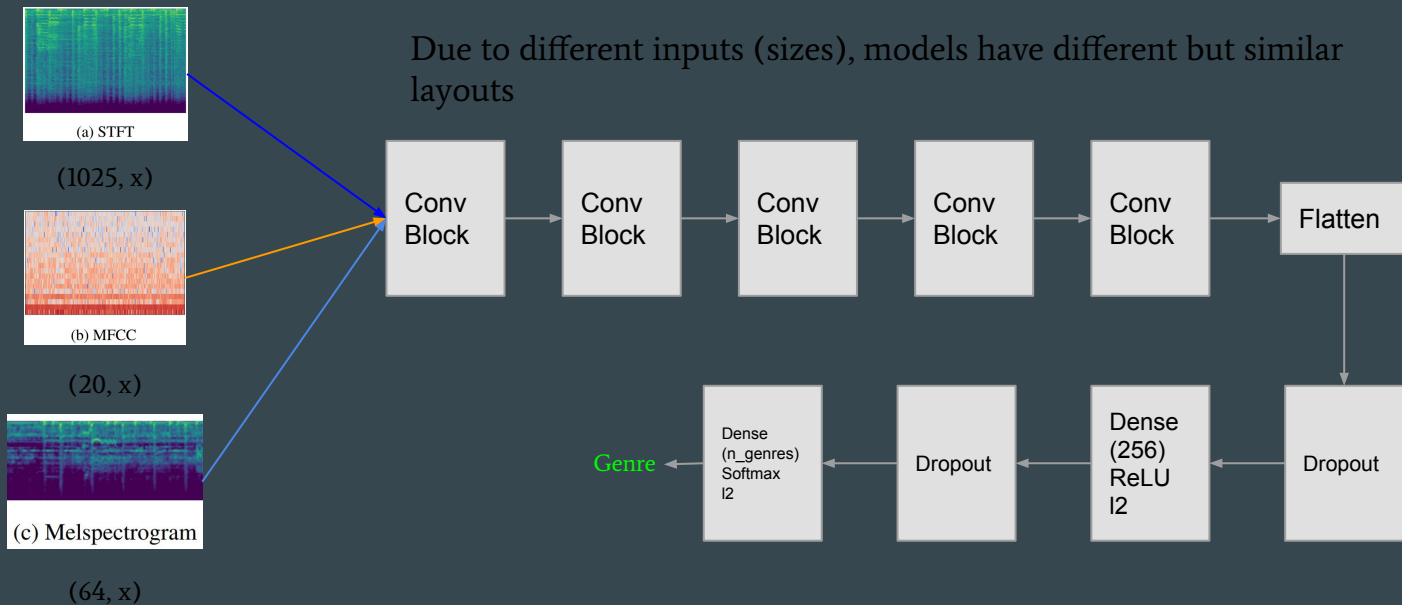
5,000: 8,000: 10,000 samples | 19,960: 31,936: 39,920 samples

64% Train | 16 % Validation | 20 % Test

# Methodology - CNN



Due to different inputs (sizes), models have different but similar layouts



# CNN Results

## GTZAN

Feature	Split	Test Accuracy
STFT	8	0.863125
STFT	5	0.855000
MELSPECTROGRAM	8	0.840000
MELSPECTROGRAM	10	0.833000
STFT	10	0.825000
MELSPECTROGRAM	5	0.815000
MFCC	10	0.759000
MFCC	8	0.701250
MFCC	5	0.610000

## Extended Ballroom

Feature	Split	Test Accuracy
STFT	5	0.903808
STFT	8	0.903413
STFT	10	0.894664
MELSPECTROGRAM	5	0.894289
MELSPECTROGRAM	8	0.870539
MELSPECTROGRAM	10	0.850576
MFCC	5	0.845190
MFCC	8	0.815435
MFCC	10	0.805361

## Comparisons

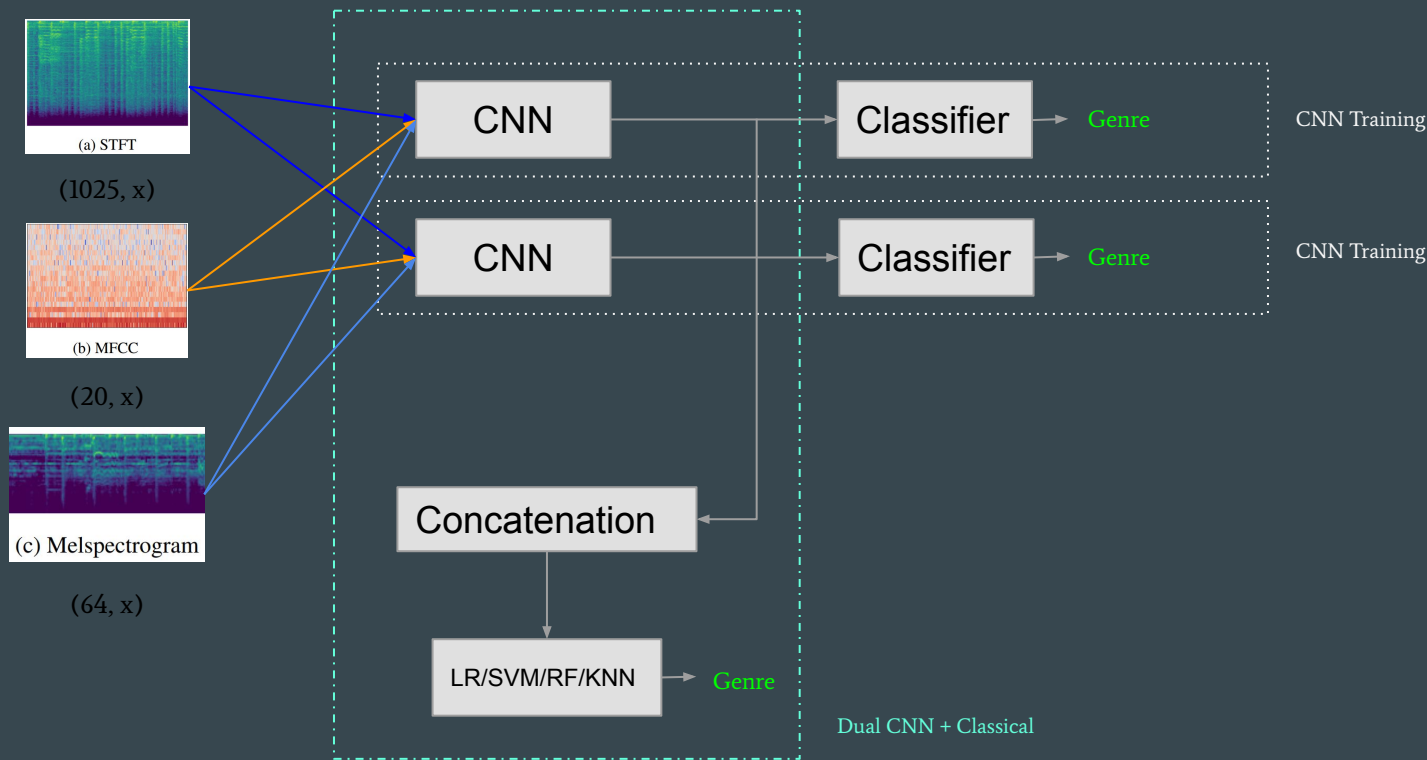
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CNN + 2-layer RNN [8]	STFT	88.8%
CNN [8]	STFT	88.0%
<b>CNN - 8 split</b>	<b>STFT</b>	<b>86.3%</b>
<b>CNN - 8 split</b>	<b>Melspectrogram</b>	<b>84.0%</b>
2-layer BRNN [4]	STFT	76.2%
<b>CNN - 8 split</b>	<b>MFCC</b>	<b>70.1%</b>

Table 2: Results on Extended Ballroom

Model	Feature	Accuracy
Broadcast NN [2]	Melspectrogram	97.2%
CNN + 1-layer RNN [8]	STFT	92.3%
CNN + 2-layer RNN [8]	STFT	92.5%
CNN [8]	STFT	92.2%
2-layer BRNN [4]	STFT	90.3%
<b>CNN - 8 split</b>	<b>STFT</b>	<b>90.3%</b>
<b>CNN - 8 split</b>	<b>Melspectrogram</b>	<b>87.0%</b>
<b>CNN - 8 split</b>	<b>MFCC</b>	<b>81.5%</b>

# Methodology - Dual CNN + Classical





# Dual CNN + Classical Results

## GTZAN

Method	Feature	Split	Test Accuracy
CNN + KNN	STFT, MELSPECTROGRAM	8	0.958125
CNN + KNN	STFT, MFCC	8	0.953125
CNN + SVM	STFT, MELSPECTROGRAM	8	0.950625
CNN + SVM	STFT, MFCC	8	0.940000
CNN + LR	STFT, MELSPECTROGRAM	8	0.932500
CNN + LR	STFT, MFCC	8	0.921250
CNN + RF	STFT, MFCC	8	0.916875
CNN + RF	STFT, MELSPECTROGRAM	8	0.916250
CNN	STFT, MFCC	8	0.908750
CNN	STFT, MELSPECTROGRAM	8	0.905625
CNN + KNN	MFCC, MELSPECTROGRAM	8	0.897500
CNN	MFCC, MELSPECTROGRAM	8	0.891875
CNN + SVM	MFCC, MELSPECTROGRAM	8	0.891250
CNN + LR	MFCC, MELSPECTROGRAM	8	0.869375
CNN + RF	MFCC, MELSPECTROGRAM	8	0.853125

## Extended Ballroom

Method	Feature	Split	Test Accuracy
CNN + SVM	STFT, MFCC	8	0.924076
CNN + RF	STFT, MFCC	8	0.919693
CNN + SVM	STFT, MELSPECTROGRAM	8	0.919537
CNN + KNN	STFT, MFCC	8	0.918284
CNN + RF	STFT, MELSPECTROGRAM	8	0.915780
CNN + LR	STFT, MFCC	8	0.914684
CNN + KNN	STFT, MELSPECTROGRAM	8	0.914058
CNN	STFT, MFCC	8	0.913118
CNN + LR	STFT, MELSPECTROGRAM	8	0.912805
CNN	STFT, MELSPECTROGRAM	8	0.911240
CNN + SVM	MFCC, MELSPECTROGRAM	8	0.898403
CNN	MFCC, MELSPECTROGRAM	8	0.891202
CNN + LR	MFCC, MELSPECTROGRAM	8	0.889167
CNN + RF	MFCC, MELSPECTROGRAM	8	0.883688
CNN + KNN	MFCC, MELSPECTROGRAM	8	0.877113

## Comparisons

Table 1: Results on GTZAN

Model	Feature	Accuracy
MusicRecNet + SVM <sup>1</sup>	Melspectrogram	97.6%
<b>Dual CNN + KNN</b>	<b>STFT, Melspectrogram</b>	<b>95.8%</b>
<b>Dual CNN + KNN</b>	<b>STFT, MFCC</b>	<b>95.3%</b>
<b>Dual CNN + SVM</b>	<b>STFT, MFCC</b>	<b>94.0%</b>
Broadcast NN <sup>2</sup>	Melspectrogram	93.9%
CNN + 1-layer RNN <sup>8</sup>	STFT	90.2%
CNN + 2-layer RNN <sup>8</sup>	STFT	88.8%
CNN <sup>8</sup>	STFT	88.0%
CNN	STFT	<b>86.3%</b>
CNN	<b>Melspectrogram</b>	<b>84.0%</b>
2-layer BRNN <sup>4</sup>	STFT	76.2%
CNN	<b>MFCC</b>	<b>70.1%</b>

Table 2: Results on Extended Ballroom

Model	Feature	Accuracy
Broadcast NN <sup>2</sup>	Melspectrogram	97.2%
CNN + 2-layer RNN <sup>8</sup>	STFT	92.5%
<b>Dual CNN + SVM</b>	<b>STFT, MFCC</b>	<b>92.4%</b>
CNN + 1-layer RNN <sup>8</sup>	STFT	92.3%
CNN <sup>8</sup>	STFT	92.2%
<b>Dual CNN + RF</b>	<b>STFT, MFCC</b>	<b>91.9%</b>
<b>Dual CNN + SVM</b>	<b>STFT, Melspectrogram</b>	<b>91.9%</b>
2-layer BRNN <sup>4</sup>	STFT	90.3%
CNN	STFT	<b>90.3%</b>
CNN	<b>Melspectrogram</b>	<b>87.0%</b>
CNN	<b>MFCC</b>	<b>81.5%</b>

# Sources

- [1] Elbir, A., & Aydin, N. (2020). Music genre classification and music recommendation by using deep learning. *Electronics Letters*, 56(12), 627-629.
- [2] Liu, C., Feng, L., Liu, G., Wang, H., & Liu, S. (2021). Bottom-up broadcast neural network for music genre classification. *Multimedia Tools and Applications*, 80(5), 7313-7331.
- [3] Marchand, U., & Peeters, G. (2016). The extended ballroom dataset.
- [4] Schuster, M., & Paliwal, K. K. (1997). Bidirectional recurrent neural networks. *IEEE transactions on Signal Processing*, 45(11), 2673-2681.
- [7] Tzanetakis, G., & Cook, P. (2002). Musical genre classification of audio signals. *IEEE Transactions on speech and audio processing*, 10(5), 293-302.
- [8] Yang, R., Feng, L., Wang, H., Yao, J., & Luo, S. (2020). Parallel recurrent convolutional neural networks-based music genre classification method for mobile devices. *IEEE Access*, 8, 19629-19637.

# Demo



```
['rock', 'disco', 'disco', 'disco', 'rock', 'disco', 'disco', 'rock', 'disco', 'hiphop', 'pop', 'rock', 'pop', 'pop', 'pop', 'pop', 'disco', 'pop', 'pop', 'disco', 'disco', 'rock', 'rock', 'disco', 'hiphop', 'rock', 'country', 'pop', 'pop', 'pop', 'disco', 'rock', 'pop', 'disco', 'reggae', 'hiphop', 'rock', 'hiphop', 'disco', 'disco', 'hiphop', 'disco', 'hiphop', 'disco', 'disco', 'disco', 'disco', 'disco', 'pop', 'disco', 'rock', 'hiphop', 'pop', 'hiphop', 'disco', 'disco', 'disco', 'hiphop', 'hiphop', 'hiphop', 'country', 'disco', 'disco', 'rock']
```

Summary:

```
{'rock': 11, 'disco': 26, 'hiphop': 11, 'pop': 13, 'country': 2, 'reggae': 1}
```

Predicted: disco

## Demo cont.



```
['rumba', 'waltz', 'waltz', 'waltz', 'waltz', 'waltz', 'waltz', 'waltz', 'rumba', 'rumba', 'viennesewaltz', 'quickstep', 'tango', 'tango', 'tango', 'tango', 'tango', 'tango', 'waltz', 'tango', 'waltz', 'samba', 'foxtrot', 'quickstep', 'tango', 'tango', 'waltz', 'quickstep', 'tango', 'tango', 'tango', 'tango', 'tango', 'jive', 'foxtrot', 'tango', 'tango', 'viennesewaltz', 'jive', 'tango', 'viennesewaltz', 'tango', 'tango', 'viennesewaltz', 'tango', 'tango', 'tango', 'tango']
```

Summary:

```
{'rumba': 3, 'waltz': 9, 'viennesewaltz': 4, 'quickstep': 3, 'tango': 24, 'samba': 1, 'foxtrot': 2, 'jive': 2}
```

Predicted: tango

*The End*